

AER General 1D-Var Retrieval Infrastructure: Transition From Research to Operations

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Components of Retrieval Infrastructure:

• Minimization procedures:

- Trade space for various retrieval approaches
 - Regression, physical..
 - · Sequential, simultaneous..
- Dependent on retrieved variables
 - Degree of non-linearity
 - Spectral dependence
- Forward models
 - Accurate fast model essential for timely retrievals
 - . OSS: state of the art in fast models
 - LBLTRM: state of the art in line-by-line models
 - Incorporates updates in spectroscopy/line shape models
 - · Used either in retrievals or for fast model training
- Cloud/Surface models/databases
 - Characteristics dependent on many intrinsic properties
 - Can be highly variable spatially (Land Surface)
 - Need relatively simple methods to account for in retrieval methods
 - Cloud mask can improve retrieval performance
 - Large impact for multi-layer cloud scenes

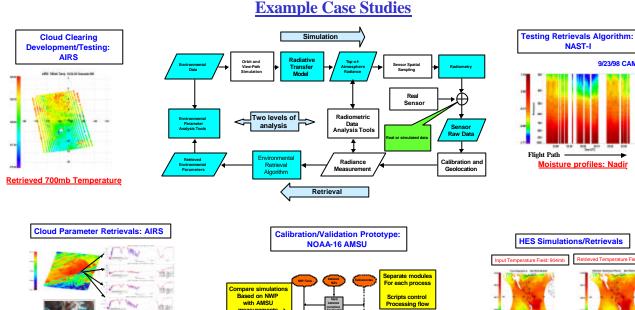
Software Development Designed for Maximum Flexibility:

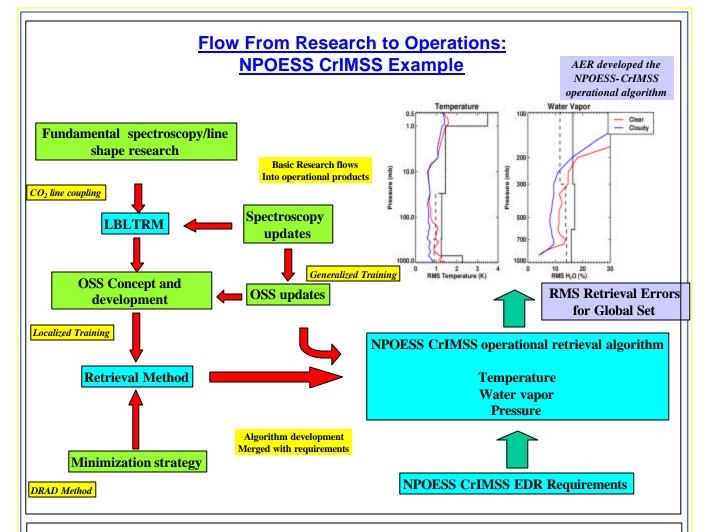
- · Modularized software design:
 - Allows for transparent updates/changes
 - Trade various methods
 - Forward model development/testing
 - Not limited to OSS/LBLTRM
 - Model trade space
 - Traceable: Configuration management
- · Standardized interface
 - Map various data products to standard format
- Use same infrastructure:
 - Simulations: simulate observations
 - •NWP, radiosonde, etc..
 - Real aircraft/on orbit observations
 - AIRS, AMSU, MODIS, SSMI, etc...

RMS Retrieval

ed: Grating

<u>Development/Testing Infrastructure Flow:</u> <u>Example Case Studies</u>





AER Unified Retrieval (UR) Algorithm

Algorithm Outline:

- Non-linear iterative physical retrieval method with radiometric and geophysical constraints
- Simultaneous retrieval of required atmospheric and surface parameters.
- Well suited for modern high resolution hyper-spectral instruments
- Ability to combine multi-sensor/multi-footprint information within the same retrieval, either simultaneously or sequentially. For example combining AIRS and AMSU for cloud-clearing
- Empirical Orthogonal Function (EOF) decomposition of retrieval parameters
 - •Reduces the dimensionality of the inversion problem.
 - •Stabilizes inversion and reduces the time needed per retrieval.
- Basic approach: Minimize maximum a posteriori cost function:

Instrument error cov Transformed Jacobian matrix
$$\Delta \widetilde{\chi}_{i+1} = (\widetilde{K}_i^T S_y^{-1} \widetilde{K}_i + \Lambda^{-1})^{-1} \widetilde{K}_i^T S_y^{-1} (y_0 - y_i + \widetilde{K}_i \Delta \widetilde{\chi}_i)$$
 Observed and calculated SDR's

- Methods developed to deal with highly non-linear problems
 - Dynamically adjust step size to ensure proper convergence.
 - DRAD Method
 - •Uses the difference between observed and simulated radiance as a proxy for linearization error

$$S_{y}(j,j) = \max \left\{ \frac{1}{\mathbf{a}} [y_{i}(j) - y_{0}(j)]^{2}, \mathbf{s}^{2}(j) \right\}$$

- •Levenberg-Marquardt Method
 - Self adjusting g parameter

$$\mathbf{g} = f(\mathbf{c}^{2}); \mathbf{c}^{2} = \sqrt{\sum_{i} \frac{(y_{c}(i) - y_{m}(i))^{2}}{\mathbf{s}^{2}(i)}}$$

- Basic retrieval methodology for the NPOESS CrlMSS operational retrievals
 - Temperature and water vapor
- NPOESS VIIRS cloud top pressure operational algorithm: water clouds
- Used in AER's internal operational AMSU calibration/validation testbed
- GOES-R trade studies

Optimal Spectral Sampling

- · OSS fast forward model
- Channel radiance for inhomogeneous atmospheric path represented by weighted sum over specific frequencies or "nodes"

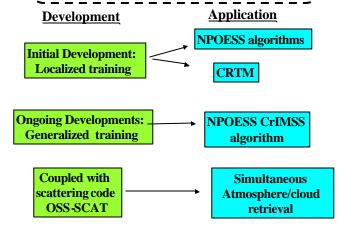
$$\overline{R} = \int_{\Lambda n} \mathbf{f}(\mathbf{n}) R(\mathbf{n}) d\mathbf{n} \cong \sum_{i=1}^{N} w_i R(\mathbf{n}_i); \qquad ?_i \in \Delta \mathbf{n}$$

 Automated search for smallest subset of <u>nodes</u> and weights for which the error is less than a prescribed tolerance

$$\left\{ \left(\mathbf{n}_{i}, w_{i} \right) \ i = 1,..., N \right\} \qquad \mathbf{e}_{N} = \sum_{s} \left[R^{s} - \sum_{i=1}^{N} w_{i} R_{\mathbf{n}_{i}}^{s} \right]^{2}$$

- In the training, radiances calculated with a line-by-line model
 - LBLRTM. GENLIN
 - globally representative ensemble of atmospheres, surface conditions, viewing angles, etc..
- Analytic Jacobians calculated with little added to overall timing
- · Training methods
 - · Localized: train each channel separately
 - Generalized: Exploit the channel-to-channel correlation
 - Decreases the total number of nodes
 - Increases the number of nodes for each channel
- · Simulation of cloudy atmospheres;
 - OSS/CHART merger

- Part of the NPOESS operational algorithms
 - · CrIMSS retrievals
 - · VIIRS cloud top pressure algorithms
- Incorporated into the NOAA Community Radiative Transfer Model (CRTM)



OSS tables in use for many instrument designs

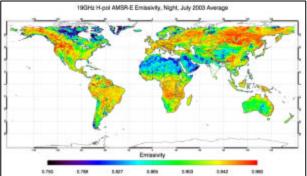
- •Microwave:
 - AMSU (NOAA and EOS) AMSR
 - SSMI. SSMI/S
- ATMS (NPOESS,NPP)
- CMIS (NPOESS)
- •IR:
 - CrIS (NPOESS,NPP)
- AIRS
- NAST-I (Airborne)
- HES (PORD)

Microwave Emissivity Database

Goals

- •Provide emissivity constraint for lower tropospheric (Precipitable Water (PW), Cloud Liquid Water (CLW)) and LST (cloudy conditions) retrieval over land
- Applications:
- Climatology (PW, CLW, LST cloudy conditions)
- Assimilation (surface emissivity model/LSM validation)
- Hydrology
- Agriculture/Land use/surface change monitoring
- Carbon studies (LST, vegetation health)
- IR cloud analysis (improved IR detection, liquid cloud underneath ice layer)

19H AMSR-E Emissivity Map 07/03 (38 km resolution – nighttime only)

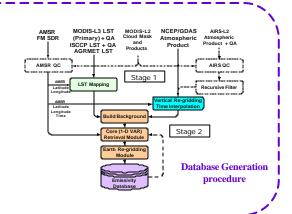


• Stage 1 (clear-sky):

- . LST and cloud mask from V.4 MODIS algorithms
- Water vapor and temperature from NCEP/GDAS (current) or AIRS product
- Emissivity retrieved on individual AMSR-E FOV's (prior to Earth gridding)
- Surface information updated at each overpass at all locations within swath

• Stage 2 (Cloudy):

- Use Stage 1 data as background in 1D-VAR retrieval algorithm (NPOESS/CMIS heritage)
- Surface emissivity constraint based on recent history at each monitored location



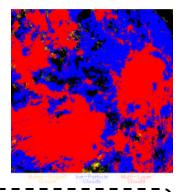
Cloud Mask: Impact on Retrievals

Cloud Mask Applied to Scene with Multiple cloud layers

- Open ocean
- Low waterdroplet clouds
- Cloud-free vegetated land
- · Thin cirrus
- Cirrostratus and cumulonimbus
- Notice instances of lower clouds (yellow) underneath thin cirrus (blue)



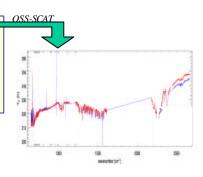
- Single-layer: low waterdroplet clouds
- Single layer: ice-particle clouds
- Multi -layer decks: thinner cirrus or deep convection



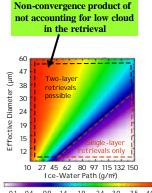
AER cloud mask algorithms part of the Air Force Weather Agency (AFWA) operational cloud product algorithms

Impact of Cloud Mask Information on Cloud Product Retrievals

- Simulated AIRS radiances for a two-layer cloud scene
- •Low cloud with top 800 mb, LWP = $80g/m^2$, and $D_{FFF} = 17\mu m$
- High cloud: top at 200 mb, base at 300 mb, vary I WP and D_{EFF}



- Retrieve assuming ONLY the single-layer cirrus cloud
- •UR has sensitivity to underlying low clouds under certain cirrus conditions

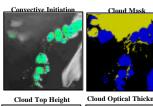


Incorporating cloud mask into retrieval can have a positive impact on the retrieval quality

-0.1 0.4 0.9 1.4 1.9 2.4 3.0 3.5 4.0 Log10 of Chi-Squared Statistic

Algorithm Testing/Development: ABI Simulations

AIB Channel 14 (11.2µm)



Cloud Top Height Cloud Optical Thickness

L2 Products

- Cloud Mask/ Phase
- Cloud top Temperature, Pressure, & Height
- Cloud Optical Thickness, Particle Size, Ice Water Path
- Convective Initiation/ Overshooting Tops

Simulations

- Simulations generated from Advanced Regional Prediction System (ARPS) NWP model fields
 - Temperature, water vapor, cloud (ice/water) amounts and surface temperature
 - 12 hours at 15 minute time steps

•OSS-SCAT forward model used

ABI Channels

Simulation/Retrieval Example:

- Simulate future GOES-R imager observations
 - Case study convective initiation during IHOP 2002
- Generate L2 products
 - Testbed for algorithm trades
- Imager products can be independent products or folded into other retrievals as constraints

ARPSI Model

•Model data provided by Ming Xueof University of Oklahoma and documented in Xue and Martin, Mon. Weather Rev., Vol. 134, 149-171, January 2006 and Xue and Martin, Mon. Weather Rev., Vol. 134, 172-190, January 2006